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Vision-based Ego-motion Computing for Intelligent Vehicles

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Abstract: In this paper, we present a method for computing velocity using a single camera onboard a road vehicle, i.e. an automobile. The use of computer vision provides a reliable method to measure vehicle velocity based on ego-motion computation. By doing so, cumulative errors inherent to odometry-based systems can be reduced to some extent. Road lane markings are the basic features used by the algorithm. They are detected in the image plane and grouped in couples in order to provide geometrically constrained vectors that make viable the computation of vehicle motion in a sequence of images. The applications of this method can be mainly found in the domains of Robotics and Intelligent Vehicles.

Keywords: Computer Vision, Egomotion, Lane Markings, Intelligent Vehicles

ACM Subject Classification Index: I. COMPUTING METHODOLOGIES
I.4 IMAGE PROCESSING AND COMPUTER VISION
I.4.8 Scene Analysis
Subject Descriptor: Motion

1. Introduction

Accurate estimation of the vehicle ego-motion with regard to the road is a key element for computer vision-based assisted driving systems. In this method, we propose the use of a single camera onboard a road vehicle in order to provide an estimation of its longitudinal velocity by computational means. There are some clear benefits derived from the use of computer vision for ego-motion computation. On the one hand, vision is not subject to slippery, contrary to odometry-based systems. This permits to reduce cumulative errors to some extent. On the other hand, it allows the integration of ego-motion data into other vision-based algorithms for intelligent vehicles, avoiding thus the need for maintaining calibration between different sensors. Some drawbacks must nonetheless be mentioned, such as the small number of feature points normally present in typical road scenes. Conversely, the problem becomes quite the opposite in urban scenes, where really cluttered images must be handled. In this case, the number of feature points increases although most of the information contained in the image is due to outliers. We propose to obtain couples of road features, mainly composed of road markings, as the main source of information for computing vehicle ego-motion. Road markings are normally found in highways and country side roads, where the estimation of vehicle velocity is most useful. Additionally, the use of lane markings allows avoiding the use of complex direct methods [1], [2], [3] for motion estimation. Instead, motion stereo techniques are considered. Motion stereo has great practical advantages as a means for a vehicle to determine its precise distance from external objects. This technique has previously been deployed in the field of indoor robotics [4]. The method is based on sampling a dynamic scene rapidly (e.g., 25 images per second) and measuring the displacements of

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features relative to each other in the image sequence. Accuracy is another advantage of the method. While the vehicle continues to approach the detected features the accuracy of the measurement improves quickly as the distance decreases. In the sequel an extension of the method for road vehicles and some experimental results will be presented.

2. Description of the method

2.1. Depth measurement

In outdoor scenes where many artificial objects and structures exist, a couple of static points that belong to the same object and are equally distant from the image plane may be observed and measured simultaneously. Points lying on the road are an example, if a camera mounted onboard an automobile is considered. In particular, the left and right edges of lane markings constitute a clear example of coupled points that can be used for computing vehicle ego-motion using perspective projection laws. Let us, then, assume that there are two road points, P_1 and P_2, with coordinates (X_1, Y_1, Z_1) and (X_2, Y_2, Z_2), where Z stands for the point depth (distance from the image plane). Let us assume that $Z_1=Z_2=Z$, which means that both points are equally distant from the image plane. The coordinates of the points in the image plane, p_1 and p_2, can then be computed as

$$p_1 = \left(u_c + f_u \cdot \frac{X_1}{Z}, v_c + f_v \cdot \frac{Y_1}{Z} \right)$$
$$p_2 = \left(u_c + f_u \cdot \frac{X_2}{Z}, v_c + f_v \cdot \frac{Y_2}{Z} \right) \tag{1}$$

where u_c and v_c represent the coordinates of the principal point in the image plane (optical center), and f_u and f_v are the camera focal length, given in pixels units, in the u (horizontal) and v (vertical) axes, respectively. Let $B=|X_1-X_2|$ be the horizontal distance between the road points and $b=|x_1-x_2|$ the horizontal distance between the corresponding image points. Based on the previous statement, $b=f_u \cdot B/Z$. Finally, let us consider that the camera is translated causing the two road points to move relative to the camera with the velocity $(dX/dt, dY/dt, dZ/dt)$ while f_u and B remain constant. In general, the derivative of b with respect to time can be computed as

$$\frac{db}{dt} = \frac{db}{dZ} \cdot \frac{dZ}{dt} = -\frac{f_u B}{Z^2} \cdot \frac{dZ}{dt} = -\frac{b}{Z} \cdot \frac{dZ}{dt} \tag{2}$$

For a couple of road points, the distance from the image plane Z can be computed under the planar road assumption as follows

$$\theta = \tan^{-1}\left(\frac{H}{Z}\right)$$
$$v = f_v \cdot \tan(\theta - \alpha) \tag{3}$$

where α stands for the camera pitch angle with respect to the horizontal line parallel to the road, v is the vertical coordinate of the coupled road points in the image plane, and H is the camera height with respect to the road plane. Let us remark that coordinate v can be directly measured from the image, while parameters H and α are supposed to be known.

2.2. Velocity estimation

Based on relations (2) and (3), an equation can be formulated for each couple i of road points equally distant from the image plane. Equation (4) shows a mathematical relation from which vehicle velocity $(v=dZ/dt)$ can be computed.

$$v = \frac{dZ}{dt} = -\frac{Z_i}{b_i} \cdot \frac{db_i}{dt} \tag{4}$$

Let N_t represent the number of road point couples found by the algorithm at frame t. The optimal estimation of vehicle velocity v can be done by optimizing the system formed by the N_t equations that can be written at each iteration of the algorithm. Based on the previous statement, the problem can be mathematically formulated as the minimization of the estimation square error SE, represented in equation 5.

$$SE = \frac{1}{N_t} \cdot \sum_{i=1}^{N_t} \left(\widehat{b_i} - b_{i,t} \right)^2 \tag{5}$$

where $\widehat{b_i}$ represents the estimation of b for couple i, and $b_{i,t}$ stands for the measurement of b for couple i at frame t. The minimization of SE must be done with respect to vehicle velocity v, as follows

$$\frac{dSE}{dv} = \frac{2}{N_t} \cdot \sum_{i=1}^{N_t} \left(\widehat{b_i} - b_{i,t} \right) \cdot \frac{d\left(\widehat{b_i} - b_{i,t} \right)}{dv} = 0 \tag{6}$$

where $\widehat{b_i}$ at frame t can be computed based on measurements carried out at frame t-1 as in equation 7

$$\widehat{b_i} = b_{i,t-1} + \frac{db_{i,t-1}}{dt} \cdot \Delta t = b_{i,t-1} - \frac{b_{i,t-1}}{Z_{i,t-1}} \cdot v_{t-1} \cdot \Delta t \tag{7}$$

where Δt stands for the total execution time and the estimation of vehicle velocity is considered to remain constant between two consecutive iterations of the algorithm. The difference between the estimation and measurement of b_i can be then expressed as follows

$$\widehat{b_i} - b_{i,t} = b_{i,t-1} - \frac{b_{i,t-1}}{Z_{i,t-1}} \cdot v_{t-1} \cdot \Delta t - b_{i,t} = \left(\frac{db_{i,t}}{dt} - \frac{b_{i,t-1}}{Z_{i,t-1}} \cdot v_{t-1} \right) \cdot \Delta t \tag{8}$$

Likewise, the derivate with respect to vehicle velocity can be computed as

$$\frac{d\left(\widehat{b_i} - b_{i,t} \right)}{dv} = -\frac{b_{i,t-1}}{Z_{i,t-1}} \cdot \Delta t \tag{9}$$

This leads to equation (10).

$$\sum_{i=1}^{N_t} \left(\frac{b_{i,t-1}}{Z_{i,t-1}} \cdot v_{t-1} - \frac{db_{i,t}}{dt} \right) \cdot \frac{b_{i,t-1}}{Z_{i,t-1}} \cdot \Delta t^2 = 0 \tag{10}$$

From equation (10), and considering that v_{t} can be approximated by v_{t-1}, the final estimation of vehicle velocity is provided by equation (11).

$$v_t \approx \frac{\sum_{i=1}^{N_t} \left(\frac{db_{i,t}}{dt} \right) \cdot \frac{b_{i,t-1}}{Z_{i,t-1}}}{\sum_{i=1}^{N_t} \left(\frac{b_{i,t-1}}{Z_{i,t-1}} \right)^2} \tag{11}$$

3. Results and Future Work

The algorithm was implemented on a PC onboard a real automobile in a test circuit. A Firewire camera was mounted on the test car, providing 640x480 Black&White images in IEEE 1394 format. The couples of road points detected by the algorithm in a real experiment are depicted in green on the left hand side of Figure 1. It must be remarked that the correspondence of road points between two consecutive images is carried out by implementing an optical flow method based on correlation techniques [5]. As can be observed, although most of the points belong to road markings other road artifacts can also provide useful information for vehicle estimation, as long as the detected features correspond to real road points. In the same figure, the instantaneous estimation of vehicle velocity at the current frame is provided (37.24 km/h), as well as the accumulated length of the path run by the car (292.78m in this example). Similarly, the estimation of vehicle velocity is provided in the right hand side of Figure 1 for the complete duration of the experiment. The vertical axis represents vehicle velocity in km/h. The red curve depicts vehicle velocity estimation without filtering, while the blue curve depicts vehicle velocity estimation using a kalman filter. The final result issued by the algorithm demonstrated to be very similar to the vehicle velocity measured by odometry means (around 40 km/h).

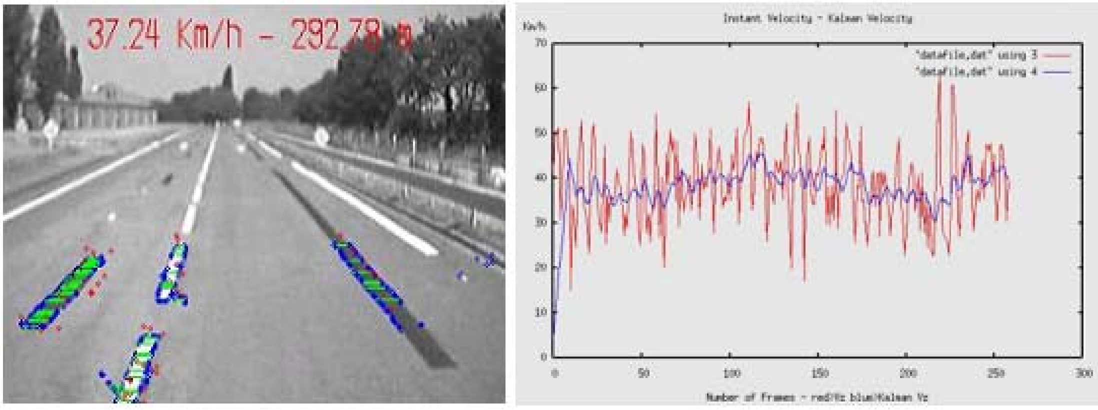

Figure 1: Detection of coupled road points (left); estimation of vehicle velocity using vision (right).

At present, the estimation of vehicle velocity is being used in the prediction stage of kalman filtering in Lane Departure Warning (LDW) Systems developed by the authors. Similarly, the estimation of vehicle ego-motion is currently being extended to a 6-component vector providing the complete ego-motion information, including vehicle longitudinal and angular displacement in X, Y, and Z. This intends to enhance the accuracy of global vehicle positioning by fusing GPS data with position estimation provided by visual means.

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